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ABSTRACT

When analysis of variance (ANOVA) or linear regression is used, results may only indicate statistical significance. This statistical significance tells the researcher very little about the data being analyzed. Additional analyses need to be used to extract all the possible information obtained from a study. While a priori and post hoc comparisons can be done with qualitative data, trend analysis is most often recommended for studies with quantitative variables with fixed intervals or effects. This paper illustrates the use of trend analysis using ANOVA and multiple regression using heuristic examples. Limitations to trend analyses are also discussed. While trend analyses can be hand calculated for simple one-way ANOVAs, it is easier and more efficient to use statistical programs such as the Statistical Package for the Social Sciences (SPSS) for more complex designs such as factorials. Three appendixes illustrate trend analysis using ANOVA, regression, and multiple analysis of variance in the SPSS. (Contains 2 figures, 6 tables, and 25 references.) (Author/SLD)

Running head: ANOVA Trend Analysis

Conducting ANOVA Trend Analyses Using Polynomial Contrasts

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Abstract

When using ANOVA or linear regression, results may only indicate statistical significance. This statistical significance tells the researcher very little about the data being analyzed. Additional analyses need to be used to extract all the possible information obtained from a study. While a priori and post hoc comparisons can be done with qualitative data, trend analyses is most often recommended for studies with quantitative variables with fixed intervals or effects. The present paper illustrates the use of trend analyses using ANOVA and multiple regression using heuristic examples. Limitations to trend analyses are also discussed.

The most common statistical analyses involve qualitative independent variables which are evaluated by looking at the difference between treatment means. These statistical analysis are either t-tests or ANOVA analyses. When employing quantitative independent variables, however, different types of analyses may be recommended. These analyses which may better describe the data without eliminating variance include linear or multiple regression and trend analysis.

While an analysis of variance can be performed sometimes graphs of the data suggest that the cell means might be related to the numerical values of the factors by some specific continuous function. In this case it is worthwhile to do a different type of analysis. This analysis is often referred to as "trend analysis," which is used to evaluate the separate contributions of linear and nonlinear components using polynomials, which are coefficients used to indicate the general form of relationships and approximate curves. These polynomials are exponential or logarithmic in form. The use of polynomials will help relate changes in the treatment means on the dependent variable to changes in the treatment variable or independent variable.

Keppel indicated that "trend analysis is a specialized form of single-degrees of freedom comparisons on a quantitative independent variable in which the treatment levels represent different amounts of a single common variable" (1982, p. 128). When different levels of a variable are represented, the experimenter is most likely interested in the overall effect of the independent variable at the various intervals. Trend analysis is most appropriate when there is a question of whether a linear or nonlinear function best represents the data. This may be discovered by using graphs.

The fundamental model for trend analysis, according to Lindman, (1974) is: $X_{ij} = \mu + a_1 (V-\overline{V}) + a_2 (V-\overline{V})^2 + a_3 (V-\overline{V})^3 + \ldots + \varepsilon_{ij}$, where X_{ij} is a polynomial, a_k is the slope, V is the numerical value of the ith factor level and V is the average of V_i. This equation for trend analysis will test for each a_k or slope in the equation the null hypothesis that $a_k = 0$ or that the best fitting straight line has a slope of 0. If a_k is very different than zero, then the null hypothesis is rejected and other non-linear trends are then evaluated. This model applies only if there are good a priori reasons to assume that the means are related to the levels by a linear function.

The primary objective of trend analysis is to study the trend of the means over the successive trials. According to Keppel (1982) trend analysis addresses three general questions about the function relating the independent and dependent variables. They are: (a) whether the data shows an overall tendency to rise or to fall over the range of treatment levels included in an experiment, (b) whether there is a possibility of a general bending of the function in an upward or downward direction, and (c) whether there is evidence of presence of more complex trends.

Test for trends are motivated by two reasons, one based on theoretical predictions and one which is purely empirical or descriptive in nature (Keppel, 1982, p. 128). The first investigates whether a particular trend fits a particular theory, such as in a priori comparisons, while the second is a post-hoc analysis which looks at the simplest function that will describe the results. For an a priori prediction, which is usually done if there are theoretical reasons to do so, the variance of the particular form of trend of interest is isolated and tested. While an ANOVA is usually done to obtain the Mean of Squares (MS) residual, the omnibus *F* is of little interest (Lee, 1975). A different way of proceeding is often followed when there is no specific theory to guide the analysis and the interest is in discovering the trend components that will jointly describe the outcome of the experiment accurately (Keppel, 1982). In this situation is a post hoc trend analysis is performed following a statistically significant omnibus *F* test. Trend analyses are also motivated when the experimenter has used quantitative or scaled independent variables such as the number of hours of food deprivation, different dosage levels of a particular drug, rates of stimulus presentation, rate of learning, and the intensity of the unconditioned stimulus in a conditioning experiment. Depending upon the nature of the experimental variables and the purpose of the experiment, some parts of the trend may be meaningful and others may not.

Trend Components

The four basic components of trend include linear, quadratic, cubic, and quartic. The linear trend is the least complex and usually the first one to be considered. A linear trend exists when the various means from the intervals fall on the regression line (Penhazur, 1982) and would involve a theory in which there is a single process changing at a constant rate (Keppel, 1982). A quadratic trend is described as a single bend either upward or downward, while the cubic and quartic trend components are more complex. These last two have two and three distinct bends respectively. That is, if X is raised to some power P, the curve associated with X_p has P-1 bends in it (Maxwell, 1990). Each particular trend can be described by an equation as shown in Table 1.

Insert Table 1 about here

The two last trend components, cubic and quartic, do not occur frequently in psychology (Keppel, 1982; Lee, 1975; Maxwell, 1990; and Winer, 1962) and are often affected by chance factors (Keppel, 1982). Keppel (1982) stated that "little is gained by way of behavioral insight when significant higher order components are found" (p. 140). It has been emphasized that before undertaking any analysis, it is helpful and necessary to plot the means of the trials for each treatment to understand and explain what the data analysis may indicate. Examples of the four main trends can be seen in Figure 1.

Insert figure 1 about here

Equal and Unequal *n* and intervals

The theory of testing for linear trends is the same for equal as for unequal *n*. When there are equal numbers of observations in each of the treatment classes, and when the treatment classes form equal steps along an ordered scale, the work of finding the degree of the best fitting curve is simplified by use of published comparisons corresponding to these curves (Winer, 1962). When there are equal *n*, trend components are orthogonal to each other (Maxwell, 1990). According to Lindman (1974):

> If the treatments form a series of equal steps along an ordered scale, then treatment variation may be subdivided into trend components through the use of

> orthogonal polynomials. The specific equations for unequal *n* take into account the different numbers of observations in the different cells. For unequal *n*, the mean of the levels is a weighted average of each level. (p. 225)

If there are unequal *n* or unequal intervals, the trend analysis will not be orthogonal, and the individual contrast coefficients will need to be computed. Unequal *n* and unequal intervals complicates trend analysis, however, many statistical packages will still automatically generate these coefficients (Maxwell, 1990).

Unequal intervals are more apt to happen when intervals are chosen randomly. Keppel (1982) has a five page appendix on how coefficients can be computed for unequal intervals. Pedhazur (1982) stated that:

> Tabled coefficients of orthogonal polynomials may be used when *n* are unequal. Under such circumstances, the coded vectors will not be orthogonal, but the hierarchical regression analysis with such vectors will yield the same results as the ones obtained from an analysis with powered vectors. Coefficients of orthogonal polynomials may also be adapted for the case of an unequally spaced variables. (p. 416)

Contrast Coefficients

When doing simple contrasts or planned comparisons in trend analysis, contrast coefficients need to be used for each level of the trend. While the coefficients for linear trends are easily derived, those for higher order trends require finding the solution to a complex set of multiple linear equations (Pedhazur, 1982). Orthogonal contrast coefficients have been derived and tabled in many statistical books (Keppel, 1982;

Lindman, 1974; Pedhazur, 1982) for cases in which there are equal n and equal intervals. These orthogonal coefficients are computed to describe the different degrees of the polynomials. The number of times the signs change in the coefficients determines the degree of the polynomial (Winer, 1962). The use of orthogonal polynomials facilitates the understanding of observed relationship between the independent and dependent variables to be divided into components of trend; otherwise, the method is similar to other methods involving orthogonal single degree of freedom comparisons. A partial list of coefficients are presented in Table 3. All sets of coefficients for orthogonal polynomials sum to zero and the sum of their cross products are also equal to zero. Each set of coefficients possess the trend components they are designed to detect (Keppel, 1982). The highest power a trend can be tested for is g-1, where g is the number of groups or intervals. Trend analysis can be performed even with one observation per cell (Lindman, 1974), but special procedures will need to be conducted.

Testing for linearity

When testing for a linear relationship, testing for linearity should follow an ANOVA. Linear trend is basically the same for both the fixed-effects and the random effects design, but power calculations are different for the random-effects model (Lindman, 1974). This paper will only address a fixed effects model. For information on power calculations, refer to Lindman (1974).

For linear regression to be applicable, the means of the treatment intervals or levels should fall on or close to the regression line. This would indicate that the effects of the independent variable have a linear trend. The deviation between the actual means and the regression line should be minimal in order to support a linear trend. To begin to test for trend, whether linear or otherwise, the following formula should be used to get the Sum of Squares for each trend $SS_{A\,trend} = s(\psi_{trend})^2/\Sigma\,(c_j)^2$. When testing for linear trend, the question will then be whether the deviation of the group means from linearity are statistically significant.

If the experimenter has a priori hypotheses concerning which polynomial components should appear, the a priori hypotheses are tested individually without first testing them pooled with other components (Lee, 1975). In a post hoc trend analysis, dividing each Sum of Squares by its degrees of freedom yields a Mean Square, which is then divided by the Mean Square error from the analysis of variance if a post hoc comparison is being done, thus yielding two F ratios. The remainder, which is described as $SS_{A\,residual} = SS_A - SS_{A\,linear}$, is then tested for statistical significance to see whether to accept the null hypothesis that the remainder can be attributed to random error. The residual Sum of Squares has $df = df_A - df_{A\,linear} = (g-1) - 1$ or g-2 degrees of freedom and the corresponding mean square is evaluated against the ANOVA residual mean square. If the F is not statistically significant and the null hypothesis is not rejected, the linear function is considered to be adequate to describe the means and the analysis is terminated.

If the F is statistically significant and the null hypothesis is rejected, the procedure is to find the best fitting function, whether quadratic, cubic, etc. Each of these functions is tested similarly by testing the remainder or residual Sum of Squares and if the null is accepted, which indicates that the residual is attributable to error, then that particular function tested is believed to represent the trend adequately. To clarify further, refer to Tables 2 and 3, where an example has been computed based on an example given by Lee

(1975, p. 294). Notice that the ANOVA was computed first and the SS_A was partitioned further into linear and nonlinear components. These components were computed by obtaining weights which were derived by multiplying trend coefficients by interval means. Sum of Squares$_{trend}$ were then computed by using the following formula: $[(W_{trend})^2 / g \times \Sigma W_a^2]$. W is the representation for the value of the contrast of treatment sums, g represents number of groups, and ΣW_a^2 represents the sum of the coefficients squared. Trends are mutually orthogonal contrasts and each has 1 df, unless you are pooling (combining various trends into one).

Insert Tables 2 and 3 about here

To find out the overall treatment variability in a trend observed in the experiment would involve calculating the ratio of component Sum of Squares ($SS_{A\,trend}$) to treatment Sum of Squares (SS_A). This can be described as: $((SS_{A\,trend} / SS_A) \times 100)$ (Lee, 1975). In the example on Table 3, this would be 546/591 x 100 = 92%, which is the percentage of variance produced by linear regression. An additional *F* ratio is obtained in our example in order to test the statistical significance of deviation from linearity. One of these *F* ratios would test the Sum of Squares due to linear regression and the other one would test the Sum of Squares due to deviation from linearity or what is known as the remainder. Additional *F* ratios are included if higher trends are tested for statistical significance. The two sums of squares derived are components of the between-treatments Sum of Squares. The Sum of Squares due to linear regression has 1 degree of freedom, while the deviation

Sum of Squares or remainder has g-2 degrees of freedom (g= number of treatments or groups) (Pedhazur, 1982). If the linear regression is what best describes the data, such as in this case, by computing r^2 ($r^2=(\Sigma xy)^2/(\Sigma x^2)(\Sigma Y^2 - (\Sigma Y)^2/N)$) between X and Y, the variance in the Y scores accounted by X can be discovered, thus illustrating how much of the trend is accounted for by linear regression.

An adaptation of an example given by Pedhazur (1982) will be used to illustrate the concept of trend analysis using multiple regression. Data presented in Table 4 illustrates this concept. Y represents the dependent variable while the independent variable, represented by vectors 1-4 using dummy coding, is group membership in the various treatment levels. When these vectors are used, the independent variable is treated as if it were a categorical variable making it possible to calculate $R^2_{y.(1234)}$. This is equivalent to a one-way analysis of variance, where R^2 is equal to N^2. Both R^2 and N^2 are equivalent to the ratio of the between-treatment Sum of Squares to the total Sum of Squares. It is now possible to test whether the deviation from linearity is statistically significant using the following formula:

$$F = \frac{(R^2_{y.1234} - R^2_{yx}) / (k_1 - k_2)}{(1 - R^2_{y.1234}) / (N - k_1 - 1)}$$

Where $R^2_{y.1234}$ = squared multiple correlation of the dependent variable, Y, and vectors 1 through 4, Where $R^2_{y.x} = r^2_{y.x}$ = squared correlation of Y with the X vector in which the independent variable is treated as continuous, k_1 is the number of vectors associated with the first R^2, k_2 is the number of vectors associated with the second R^2, and N is the number of subjects. The degrees of freedom for the *F* ratio are $k_1 - k_2$ and $N-k_1 - 1$ for the numerator and the denominator respectively.

$R^2_{y \cdot 1234}$ must be larger than R^2_{yx} when there is a deviation from linearity, unless the regression of Y on X is exactly linear, in which case they will be equal. (Pedhazur, 1982, p. 403)

If there is a deviation from linearity, this deviation is what is tested by the above.

When no restriction of trend is placed on the data the calculation for the Sum of Squares for the overall regression will equal $(R^2_{y.\ 1234})(\Sigma y^2)$. The Sum of Squares due to the deviation from linearity can be obtained by subtracting the regression Sum of Squares due to linearity from the overall regression Sum of Squares. The Sum of Squares due to errors is always the proportion of variance not accounted for multiplied by the total Sum of Squares (Pedhazur, 1982).

Curvilinear Regression Analysis

A heuristic example will be used to illustrate curvilinear regression analysis. This example involves using a multiple regression analysis derived using SPSS. The output for this example is referenced as Appendix B. Appendix C is provided for the reader as a reference and will not be discussed in this paper. This output describes a curvillinear analysis using MANOVA in SPSS.

The curvilinear regression analysis using multiple regression in Appendix B first evaluates whether there is a statistically significant deviation from linearity in the data. If there is a deviation from linearity, a multiple regression analysis is then conducted to test whether there is some trend in the data. This analysis, however, will not indicate what type of trend exists. To discover the type of trend involved, it is necessary to test for nonlinear models, such as quadratic, cubic, and quartic trend analysis. While there are two categories of nonlinear models (intrinsically linear models and intrinsically nonlinear models) according to Pedhazur (1982), the present paper will only describe an intrinsically linear model, which is linear in its parameters but nonlinear in the variables. These nonlinear variables can be reduced to a linear model by using an appropriate transformation, expressing variables as logarithms, taking square roots of variables or raising variables to powers (using polynomials). Refer to Table 5 to observe how groups are raised to powers when doing regression using SPSS.

Insert Table 5 about here

Curvilinear Regression and Orthogonal Polynomials

Curvilinear and linear regression methods are similar with the exception that the curvilinear regression analysis uses a polynomial regression equation, which means that the independent variable is raised to a certain power. When trend analysis is performed, researchers are attempting to fit the data with a polynomial function. The simplest polynomial function is a first-order polynomial or linear equation, which has already been illustrated, described by $Y=b_1+ b_2X$ where Y refers to the values of the dependent variable, b is a constant, and X refers to values of the independent variable. A more familiar linear equation is $Y=a_1 + b_iX$. The quadratic, or second order, equation is $Y=b_0 + b_1X^1 + b_2X^2$ where b's are a different set of constants and X and Y refer to values of the independent and dependent variables, respectively. The equations are characterized by the last term on the right of the equals sign. For example, b_2X^2 refers to quadratic, b_3X^3 refers to cubic, etc. Each comparison represents the pure form of a different order of polynomial, one for linear order, one for quadratic order, and so on (Keppel, 1982). The number of terms in a polynomial can vary, and is usually characterized by g-1, where g is the number of cell means or distinct values (intervals) in the independent variable. Notice that in Table 5, eventhough there are four groups, there are only 3 sets of polynomials generated. Pedhazur (1982) indicated that when the highest order polynomial has been found, the regression equation will yield predicted Y's that are equal to the means of the different Y vectors, thus resulting in the smallest possible value for the residual Sum of Squares. Pedhazur (1982) also indicated that "when the highest-degree polynomial is used with any set of data the resulting R^2 is equal to η^2, since both analyses permit as many bends in the curve as there are degrees of freedom minus one for the between-treatments Sum of Squares" (p. 405). Testing the highest-degree polynomial possible is equivalent to testing whether the means of the treatments differ from each other when a one-way analysis of variance is applied (Pedhazur,1982). Notice how the ANOVA results generated through multiple regression on page 5 of Appendix B is identical to the results obtained by calculating a one way ANOVA and by results on SPSS using ANOVA.

The objective of trend analysis is to find the lowest degree polynomial which best represents the data. Polynomial regression is done similarly as multiple regression with the exception that powered vectors are included, and the analysis is done hierarchically or in a series of steps. The approach taken is first to use the polynomial function of the smallest order that will fit the cell means, leaving only variations between the means and the fitted function that can be attributed to sampling variability (Lee, 1975). Constants are chosen so that the function lies as close as possible to the cell means. The Sum of Squares for the quantitative factor is divided into a component accountable to the linear function derived and a component not accountable, that is the remainder. This remainder is also called Sum of Squares Change or residual, and is derived by subtracting successively each element in the Sum of Squares from each trend from the Sum of Squares between. Notice that in Appendix B, the $SS_{lin} = 549.01$ and $SS_{residual} = 99.92$. The remainder is tested for Statistical significance to see whether to accept the null hypothesis that the remainder can be attributed to random error. If the null hypothesis is accepted, the linear function is considered to be adequate to represent the cell means as done in the univariate linear trend example described earlier. If the null hypothesis is rejected, the procedure is to find the best-fitting quadratic function. In this example, the null hypothesis is rejected ($p = .0000$) (Refer to Appendix B). Then the next step is to find the *SS* that is associated with the quadratic function so the remainder continues to decrease. This residual *SS* is then tested for statistical significance, and if the residual is attributable to error (if the null is accepted), the quadratic is taken to represent the trend adequately. Otherwise, the best fitting cubic function is found and so on. Because there are combinations of trends, it is usually necessary to test higher-order trends regardless of whether the linear trend is statistically significant (Maxwell, 1990).

To further explain the regression equation produced by the example on Appendix B, Table 6 was partially derived from the computer output and some of it was hand calculated to explain certain characteristics of trend analysis. Most of the information on this table was derived by the computer output, including the $MS_{residual}$, which was obtained from the last step of the analysis. The R square and SS_{Change} needed to be calculated and were derived by subtracting the R square and *SS* from each consecutive trend's R square and *SS* respectively, and calculating the new *F* calculated, which is derived from dividing the MS_{trend} by the $MS_{residual}$. The elements in the column labeled Sum of Squares parallel those reported under R square, except the R square is the proportion of variance accounted for, whereas the *SS* provides the same information but is expressed by Sum of Squares (Pedhazur, 1982). From looking at the information in Table 6, it can be seen that the linear component accounts for about 85% and the quadratic component accounts for about 6% of the variance of the independent variable. Pedhazur (1982) indicated that "the *b's* on the output are partial regression coefficients, and are equivalent to a test of the proportion of variance incremented by the variable with which it is associated when the variable is entered last into the analysis" (p. 410). Only the *b* for the highest degree polynomial is meaningful, even when *b's* associated with lower trends are not statistically significant, thus, all vectors are retained even if not statistically significant (Pedhazur, 1982).

Squared or powered vectors tend to be highly intercorrelated and tend not to have a meaningful squared semipartial correlation with the dependent variable. It might be useful to transform X by subtracting the mean, standardization, or using orthogonal polynomials in order to reduce the high multicollinearity that generally exist among powered vectors (Pedhazur, 1982). Because statistical significance tests for polynomial regression should proceed hierarchically, the *b* for the highest-degree polynomial is what is relevant in polynomial regression analysis. The regression equation is calculated only with the terms that are to be retained when statistically significant, this includes the highest order polynomial found to be statistically significant and all lower-order polynomials, whether they are statistically significant or not. The vectors associated with the lower polynomials *b's* should not be deleted.

With analysis of orthogonal polynomials, each *b* weight is independently interpretable, since each *b* tests separate trend components and can be obtained directly from a computer output. The higher order polynomials which were not statistically significant are pooled with the Sum of Squares residual. This results in a smaller mean square error term. The relatively small increase in the residual Sum of Squares is offset by the increase in the degrees of freedom for the Sum of Squares residual. The regression equation can be used to calculate predicted scores. It is also possible to use the regression equation to predict performance on the dependent variable for values not used originally in the study, as long as such values are within the range of those originally used. This is called interpolation. Extrapolation, on the other hand is dangerous and should be avoided because one should not engage in predictions for values of the variable that are outside the range used in the initial study (Pedhazur, 1982).

The regression equation using orthogonal polynomials will have a mean of zero, and will always be equal to the mean of the dependent variable and this will be the value of the intercept, *a*. Each dependent variable score is expressed as a composite of the mean of the dependent variable and the contribution of those components of the trend that are included in the regression equation. The *b* weights can be read from the computer output and combined with each vector represented, such that $Y' = a + b_1X + b_2X^2 + \ldots\ldots b_iX^i$. When using the regression equation for purposes of prediction, the values inserted in it are the coded values that correspond to a given level and a given degree of the polynomial (Pedhazur, 1982).

Factorial Designs

Trend analysis can also be used in factorial designs which consist of either continuous or categorical independent variables. When the independent variables are continuous, each variable should be coded with orthogonal polynomial coefficient as if it is the only one in the design and then generate cross product vectors by multiplying the vectors of one variable by those of the other (Pedhazur, 1982). The cross-product vectors represent the interactions. Trend analysis can be applied to both main effects and interactions when appropriate.

When applied to main effects, trend analysis is essentially identical to the single-factor case, but the procedure is different when it is applied to interactions. Trend analysis for main effects is simply a set of planned comparisons, using the coefficients for the linear, quadratic, and cubic trends (Lindman, 1974). Estimates of the variance of each trend component are found using $SS_{bet} = \Sigma_k (C'_k)^2$, where C_k represents individual contrasts, and estimates of proportion of variance accounted for is found using $\varpi_k^2 = ((C'_k)^2 - MS_w)/(SS_t + MS_w)$. These equations apply for fixed factor designs. If the factor was random the denominator would change from MS_w to MS_{ab}. For further information refer to Lindman (1974, p. 250). Trend analysis should be performed with each main effect in the same way the analysis was performed with simple effects in a one way design.

Trend analysis used for interactions, uses the same computational formulas required for interaction comparisons, but attempts to describe interaction in terms of simple trend components (Keppel, 1982). When analyzing interactions, the slopes of best fitting functions are drawn from the means in the different levels of the factor being tested.

According to Keppel (1982), the slopes of best fitting functions drawn through the cell means at the different levels of the factor are being compared. If the Sum of squares interaction is due to the interaction of the linear functions or the differences in slope, the source of the interaction will be pinpointed. Given the set of means in a AXB factorial experiment, the line joining these may have an irregular shape. The slope of the best fitting line defines the linear or nonlinear trend.

> Global differences between shapes of profiles for simple main effects of factor B give rise to the AB interaction. Differences between the linear trends of such profiles define that part of the AB interaction which is called AB (linear). Differences in other profiles will define that part of the AB interaction for each respective trend. In general the overall variation due to AB interaction may be divided into nonoverlapping, additive parts, which arise from specific kinds of differences in the shapes of profiles, linear, quadratic, etc.(Winer, 1962, p. 354)

The hypothesis involved in a AXB interaction is that the profiles of the simple main effects have equal slopes and that the best fitting functions if linear is parallel and if quadratic have equal quadratic trends. Figure 2 shows an example (Keppel, 1982) of an interaction.

Insert Figure 2 about here

At level b_1 the means rise and fall as factor A increases, describing a reasonable quadratic trend. All that is necessary to perform a trend analysis for the interactions are the use of coefficients and to substitute the necessary quantities in the computational formulas. The maximum number of orthogonal interaction comparisons that can be extracted from any given interaction Sum of Squares (SS_{AXB}) is equal to the degrees of freedom associated with this source of variability; that is, $df_{AXB}=(a-1)(b-1)$.

Limitations of Trend Analysis

There are various limitations when performing trend analysis. First of all, is trend analysis appropriate? Lindman (1974) warned that if it is found that a large number of terms or intervals have to be incorporated in the function, a polynomial function may not be appropriate for that particular experiment and trend analysis should not be used. If trend analyisis is appropriate, then Keppel (1982) warned that there are various things that need to be thought about and addressed. They are: (a) the analysis done by trend analysis using particular intervals is limited to that particular experiment, since there are probabilities that if other points would have been selected the results could have varied; (b) results can be described for that particular experiment and extrapolation outside the two extreme values on the independent variable is inappropriate; (c) trend analysis assumes equal number of subjects in each of the treatment conditions and equal intervals; (d) in some areas of psychology, certain phenomena are better described by an exponential function than by a logarithmic function.

Conclusion

Trend analyses are helpful in describing quantitative data when set intervals are used. These analyses can be applied to simple one-way designs as well as with more complex factorials. While trend analysis can be hand calculated for simple one-way ANOVA's, it is easier and more efficient to use statistical programs such as SPSS for more complex designs such as factorials. There are various limitations, which need to be addressed when interpreting trend analysis results.

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Table 1

Polynomial Equations

	Polynomial Equation	Number of bends in Regression curve
Linear	$Y' = a + b_1x$	Zero
Quadratic	$Y' = a + b_1x + b_2x^2$	One
Cubic	$Y' = a + b_1x + b_2x^2 + b_3x^3$	Two
Quartic	$Y' = a + b_1x + b_2x^2 + b_3x^3 + b_4x^4$	Three
Quintic	$Y' = a + b_1x + b_2x^2 + b_3x^3 + b_4x^4 + b_5x^5$	Four

Table 2

Calculations of Trend Analysis using ANOVA

	A1	A2	A3	A4
	2	9	14	19
	3	13	18	20
	4	14	18	20
	6	17	17	21
X_A	15	53	67	80
X_A	3.75	13.25	16.75	20

Analysis of Variance

Source	Sum of Squares	DF	Mean Square	F	Sig. F
A	591.69	3	197.23	43.63	.0000
Residual	54.25	12	4.52		
Total	645.94	15			

(continue to partition SS_A into linear and non-linear components).

Table 3

Calculations of Trend Analysis using ANOVA Cont.

Coefficients of Orthogonal polynomials for this example:

	w_1	w_2	w_3	w_4	Σw_a^2
Linear	-3	-1	1	3	20
Quadratic	1	-1	-1	1	4
Cubic	-1	3	-3	1	20

Sum of Squares $_{linear}$ = (-3)(15) + (-1)(53) + (1)(67) + (3)(80)
= -45 -53 + 67 +240 = 209
= 209^2 /4 x 20 = 546.0125

Sum of Squares $_{Quad}$ = (1)(15) + (-1)(53) + (-1)(67) + (1)(80)
= 15-53+67+80 = -25
= -25^2/4 x 4 = 39.0625

Sum of Squares $_{cub}$ = (-1)(15) + (3)(53) + (-3)(67) + (1) (80)
= -15+159-201+80 = 23
= 23^2/4 x 20 = 6.6125

Note that SS_{lin}, SS_{quad}, and SS_{cub} are mutually orthogonal contrasts. Each component has 1 df. When only testing two components, *SS* are formed by pooling SS_{trends} for separate contrasts (ie. Quad and cubic).

ANOVA and Trend Analysis

Analysis of Variance

Source	Sum of Squares	DF	Mean Square	F	Sig. F
A	591.69	3	197.23	43.63	.0000
Lin	546.01	1	546.01	120.77	.0000
Quad	39.06	1	39.06	8.64	.0250
Cubic	6.61	1	6.61	1.46	
Residual	54.25	12	4.52		
Total	645.94	15			

Numbers have been rounded off.

Table 4

Coefficients for group assignment

Treatment/ Group	Y	X	1	2	3
1	2	1	1	0	0
	3	1	1	0	0
	4	1	1	0	0
	6	1	1	0	0
2	9	2	0	1	0
	13	2	0	1	0
	14	2	0	1	0
	17	2	0	1	0
3	14	3	0	0	1
	18	3	0	0	1
	18	3	0	0	1
	17	3	0	0	1
4	19	4	0	0	0
	20	4	0	0	0
	20	4	0	0	0
	21	4	0	0	0

Table 5

	x	y1	x2	x3	x4
1	1	2	1.00	1.00	1.00
2	1	3	1.00	1.00	1.00
3	1	4	1.00	1.00	1.00
4	1	6	1.00	1.00	1.00
5	2	9	4.00	8.00	16.00
6	2	13	4.00	8.00	16.00
7	2	14	4.00	8.00	16.00
8	2	17	4.00	8.00	16.00
9	3	14	9.00	27.00	81.00
10	3	18	9.00	27.00	81.00
11	3	18	9.00	27.00	81.00
12	3	17	9.00	27.00	81.00
13	4	19	16.00	64.00	256.00
14	4	20	16.00	64.00	256.00
15	4	20	16.00	64.00	256.00
16	4	21	16.00	64.00	256.00

Table 6

Trend Analysis using Multiple Regression

Step	Variable Entered	R Square	R Square Change	Sum of Squares	Sum of Squares Change	DF	Mean Square	F
1	X (Linear)	.84530	.84530	546.01250	546.01250	1	546.01250	120.770 *
2	X2 (Quadratic)	.90578	.06048	585.07500	39.0625	1	39.0625	8.640 **
3	X3 (Cubic)	.91601	.01023	591.68750	6.6125	1	6.6125	1.462
	Residual			54.25		12	4.52083	

*Statistically Significant at .0000 level
**Statistically Significant at .025 level

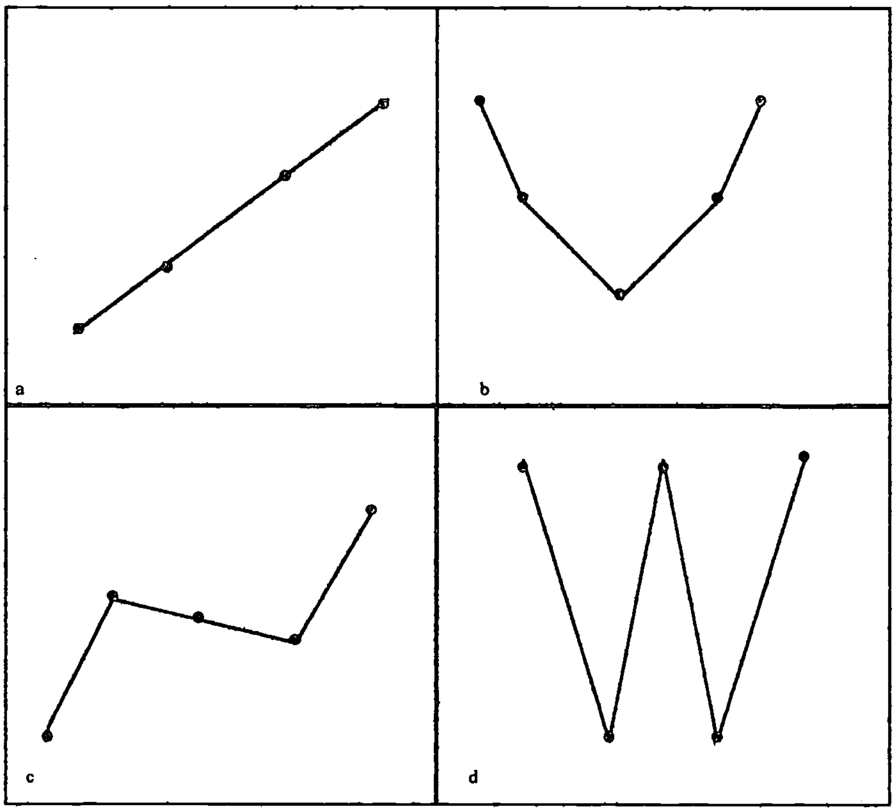

Figure 1. Graphs of polynominal trends. (a) Linear (b) Quadratic (c) Cubic (d) Quartic

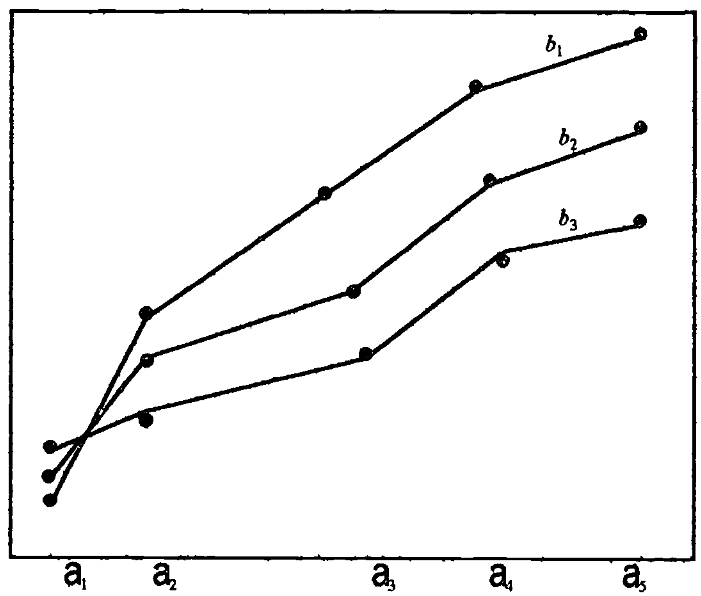

Figure 2. Example of A_{linear} X B interaction

Appendix A

Trend Analysis Using ANOVA in SPSS

```
ONEWAY
  var00002 BY var00001(1 5)
  /HARMONIC NONE
  /FORMAT NOLABELS
  /MISSING ANALYSIS .
```

- - - - - O N E W A Y - - - - -

Variable VAR00002
By Variable VAR00001

Analysis of Variance

Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	3	591.6875	197.2292	43.6267	.0000
Within Groups	12	54.2500	4.5208		
Total	15	645.9375			

```
ONEWAY
  var00002 BY var00001(1 5)
  /POLYNOMIAL= 1
  /HARMONIC NONE
  /FORMAT NOLABELS
  /MISSING ANALYSIS .
```

- - - - - O N E W A Y - - - - -

Variable VAR00002
By Variable VAR00001

Analysis of Variance

Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	3	591.6875	197.2292	43.6267	.0000
Linear Term	1	546.0125	546.0125	120.7770	.0000
Deviation from Linear	2	45.6750	22.8375	5.0516	.0256
Within Groups	12	54.2500	4.5208		
Total	15	645.9375			

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```
ONEWAY
  var00002 BY var00001(1 5)
  /POLYNOMIAL= 1
  /HARMONIC NONE
  /FORMAT NOLABELS
  /MISSING ANALYSIS .
ONEWAY
  var00002 BY var00001(1 5)
  /POLYNOMIAL= 2
  /HARMONIC NONE
  /FORMAT NOLABELS
  /MISSING ANALYSIS .
```

- - - - - O N E W A Y - - - - -

Variable VAR00002
By Variable VAR00001

Analysis of Variance

Source	D.F.	Sum of Squares	Mean Squares	F Ratio	F Prob.
Between Groups	3	591.6875	197.2292	43.6267	.0000
Linear Term	1	546.0125	546.0125	120.7770	.0000
Deviation from Linear	2	45.6750	22.8375	5.0516	.0256
Quad. Term	1	39.0625	39.0625	8.6406	.0124
Deviation from Quad.	1	6.6125	6.6125	1.4627	.2498
Within Groups	12	54.2500	4.5208		
Total	15	645.9375			

Appendix B

Trend Analysis Using Regression in SPSS

```
Title 'Linear Trend'.
SET BLANKS=-99999 UNDEFINED=WARN.
DATA LIST
  File = 'a:trendlanalysis.dat' Fixed Records = 1 table
  /X 1 Y1 3-4.
Subtitle 'lpolynomials'.
Compute X2=X**2.
Compute X3=X**3.
Compute X4=X**4.
List Variables = all/cases = 500/Format = numbered.
Regression Variables = Y1 X X2 X3 X4/Descriptives=All/
  Criteria=Tolerance (.000001)/Dependent=Y1/Enter X/Enter X2/
  Enter X3/ Enter X4.
Regression Variables=Y1 X/Descriptives=All/
  Criteria=Tolerance (.000001)/Dependent=Y1/Enter X.
```

	X	Y1	X2	X3	X4
1	1	2	1.00	1.00	1.00
2	1	3	1.00	1.00	1.00
3	1	4	1.00	1.00	1.00
4	1	6	1.00	1.00	1.00
5	2	9	4.00	8.00	16.00
6	2	13	4.00	8.00	16.00
7	2	14	4.00	8.00	16.00
8	2	17	4.00	8.00	16.00
9	3	14	9.00	27.00	81.00
10	3	18	9.00	27.00	81.00
11	3	18	9.00	27.00	81.00
12	3	17	9.00	27.00	81.00
13	4	19	16.00	64.00	256.00
14	4	20	16.00	64.00	256.00
15	4	20	16.00	64.00	256.00
16	4	21	16.00	64.00	256.00

Number of cases read: 16   Number of cases listed: 16

* * * * M U L T I P L E   R E G R E S S I O N * * * *

Listwise Deletion of Missing Data

	Mean	Std Dev	Variance	Label
Y1	13.438	6.562	43.063	
X	2.500	1.155	1.333	
X2	7.500	5.865	34.400	
X3	25.000	25.245	637.333	
X4	88.500	104.594	10940.000	

N of Cases = 16

Correlation, Covariance, 1-tailed Sig, Cross-Product:

	Y1	X	X2	X3	X4
Y1	1.000	.919	.862	.802	.752
	43.063	6.967	33.167	132.867	516.167
	.	.000	.000	.000	.000
	645.938	104.500	497.500	1993.000	7742.500
X	.919	1.000	.984	.951	.916
	6.967	1.333	6.667	27.733	110.667
	.000	.	.000	.000	.000
	104.500	20.000	100.000	416.000	1660.000
X2	.862	.984	1.000	.991	.972
	33.167	6.667	34.400	146.667	596.000
	.000	.000	.	.000	.000
	497.500	100.000	516.000	2200.000	8940.000
X3	.802	.951	.991	1.000	.995
	132.867	27.733	146.667	637.333	2626.667
	.000	.000	.000	.	.000
	1993.000	416.000	2200.000	9560.000	39400.000
X4	.752	.916	.972	.995	1.000
	516.167	110.667	596.000	2626.667	10940.000
	.000	.000	.000	.000	.
	7742.500	1660.000	8940.000	39400.000	164100.000

* * * * M U L T I P L E R E G R E S S I O N * * * *

Equation Number 1 Dependent Variable.. Y1

Descriptive Statistics are printed on Page 2

Block Number 1. Method: Enter X

Variable(s) Entered on Step Number
1.. X

Multiple R	.91940
R Square	.84530
Adjusted R Square	.83425
Standard Error	2.67161

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	1	546.01250	546.01250
Residual	14	99.92500	7.13750

F = 76.49912 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
X	5.225000	.597390	.919403	8.746	.0000
(Constant)	.375000	1.636020		.229	.8220

------------- Variables not in the Equation -------------

Variable	Beta In	Partial	Min Toler	T	Sig T
X2	-1.396528	-.625235	.031008	-2.889	.0127
X3	-.765858	-.599831	.094895	-2.703	.0181
X4	-.563797	-.574076	.160390	-2.528	.0252

End Block Number 1 All requested variables entered.

```
           * * * *   M U L T I P L E   R E G R E S S I O N   * * * *

Equation Number 1    Dependent Variable..   Y1

Block Number  2.  Method:  Enter      X2


Variable(s) Entered on Step Number
   2..    X2


Multiple R           .95172
R Square             .90578
Adjusted R Square    .89128
Standard Error      2.16373

Analysis of Variance
                    DF      Sum of Squares      Mean Square
Regression           2           585.07500        292.53750
Residual            13            60.86250          4.68173

F =      62.48490       Signif F =  .0000

------------------ Variables in the Equation ------------------

Variable              B        SE B       Beta         T  Sig T

X             13.037500    2.747597   2.294109     4.745  .0004
X2            -1.562500     .540933  -1.396528    -2.889  .0127
(Constant)    -7.437500    3.011786               -2.469  .0282

------------- Variables not in the Equation -------------

Variable     Beta In  Partial  Min Toler        T  Sig T

X3          3.686806  .329616  2.461E-04    1.209  .2498
X4          1.527480  .329616  8.482E-04    1.209  .2498

End Block Number   2   All requested variables entered.
```

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```
           * * * *   M U L T I P L E   R E G R E S S I O N   * * * *

Equation Number 1    Dependent Variable..   Y1

Block Number  3.  Method:  Enter      X3


Variable(s) Entered on Step Number
   3..    X3


Multiple R           .95709
R Square             .91601
Adjusted R Square    .89502
Standard Error      2.12623

Analysis of Variance
                    DF      Sum of Squares      Mean Square
Regression           3           591.68750        197.22917
Residual            12            54.25000          4.52083

F =      43.62673       Signif F =  .0000


------------------ Variables in the Equation ------------------

Variable              B          SE B         Beta          T  Sig T

X             29.041667     13.505668     5.110240      2.150  .0526
X2            -8.750000      5.966704    -7.820556     -1.466  .1682
X3              .958333       .792397     3.686806      1.209  .2498
(Constant)   -17.500000      8.830876                  -1.982  .0709


------------- Variables not in the Equation -------------

Variable     Beta In  Partial  Min Toler          T  Sig T

X4              .         .       .000000        .     .


End Block Number   3   All requested variables entered.
```

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* * * * M U L T I P L E   R E G R E S S I O N * * * *

```
Equation Number 1    Dependent Variable..   Y1

Block Number  4.  Method:  Enter      X4


End Block Number   4   Tolerance = 1.00E-06 Limits reached.
No variables entered for this block.
```

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* * * * M U L T I P L E   R E G R E S S I O N * * * *

Listwise Deletion of Missing Data

	Mean	Std Dev	Variance	Label
Y1	13.438	6.562	43.063	
X	2.500	1.155	1.333	

N of Cases = 16

Correlation, Covariance, 1-tailed Sig, Cross-Product:

	Y1	X
Y1	1.000	.919
	43.063	6.967
	.	.000
	645.938	104.500
X	.919	1.000
	6.967	1.333
	.000	.
	104.500	20.000

* * * * M U L T I P L E R E G R E S S I O N * * * *

Equation Number 1 Dependent Variable.. Y1

Descriptive Statistics are printed on Page 7

Block Number 1. Method: Enter X

Variable(s) Entered on Step Number
1.. X

Multiple R	.91940
R Square	.84530
Adjusted R Square	.83425
Standard Error	2.67161

Analysis of Variance

	DF	Sum of Squares	Mean Square
Regression	1	546.01250	546.01250
Residual	14	99.92500	7.13750

F = 76.49912 Signif F = .0000

------------------ Variables in the Equation ------------------

Variable	B	SE B	Beta	T	Sig T
X	5.225000	.597390	.919403	8.746	.0000
(Constant)	.375000	1.636020		.229	.8220

End Block Number 1 All requested variables entered.

Appendix C

Trend Analysis Using MANOVA in SPSS

```
RENAME VARIABLES (var00001=A1).
RENAME VARIABLES (var00002=A2).
RENAME VARIABLES (var00003=A3).
RENAME VARIABLES (var00004=A4).
MANOVA
  a1  a2  a3  a4
  /WSFACTORS factor1(4)
  /CONTRAST (factor1)=Polynomial
  /CINTERVAL INDIVIDUAL(.95)  UNIVARIATE
  /METHOD UNIQUE
  /ERROR WITHIN+RESIDUAL
  /PRINT
    SIGNIF( UNIV MULT AVERF )
    PARAM( ESTIM ).
```

Manova

- -

* * * * * * A n a l y s i s   o f   V a r i a n c e * * * * * *

```
4 cases accepted.
0 cases rejected because of out-of-range factor values.
0 cases rejected because of missing data.
1 non-empty cell.

1 design will be processed.
```

- -

* * * * * * A n a l y s i s   o f   V a r i a n c e -- design 1 * * * * * *

Tests of Between-Subjects Effects.

Tests of Significance for T1 using UNIQUE sums of squares

Source of Variation	SS	DF	MS	F	Sig of F
WITHIN+RESIDUAL	38.19	3	12.73		
CONSTANT	2889.06	1	2889.06	226.96	.001

- -

Estimates for T1
--- Individual univariate .9500 confidence intervals

CONSTANT

Parameter	Coeff.	Std. Err.	t-Value	Sig. t	Lower -95%	CL- Upper
1	26.8750000	1.78390	15.06532	.00063	21.19784	32.55216

- -

```
* * * * * * A n a l y s i s   o f   V a r i a n c e -- design   1 * * * * * *

Tests involving 'FACTOR1' Within-Subject Effect.


 Mauchly sphericity test, W =      .03298
 Chi-square approx. =             5.87582 with 5 D. F.
 Significance =                      .318

 Greenhouse-Geisser Epsilon =      .59825
 Huynh-Feldt Epsilon =            1.00000
 Lower-bound Epsilon =             .33333

AVERAGED Tests of Significance that follow multivariate tests are equivalent to
univariate or split-plot or mixed-model approach to repeated measures.
Epsilons may be used to adjust d.f. for the AVERAGED results.

 - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - - -
```

* * * * * * A n a l y s i s   o f   V a r i a n c e -- design   1 * * * * * *

EFFECT .. FACTOR1
Multivariate Tests of Significance (S = 1, M = 1/2, N = -1/2)

Test Name	Value	Exact F	Hypoth. DF	Error DF	Sig. of F
Pillais	.99978	1505.00000	3.00	1.00	.019
Hotellings	4515.00000	1505.00000	3.00	1.00	.019
Wilks	.00022	1505.00000	3.00	1.00	.019
Roys	.99978				

Note.. F statistics are exact.

- -

EFFECT .. FACTOR1 (Cont.)
Univariate F-tests with (1,3) D. F.

Variable	Hypoth. SS	Error SS	Hypoth. MS	Error MS	F	Sig. of F
T2	546.01250	4.03750	546.01250	1.34583	405.70588	.000
T3	39.06250	6.18750	39.06250	2.06250	18.93939	.022
T4	6.61250	5.83750	6.61250	1.94583	3.39829	.162

- -

* * * * * * A n a l y s i s   o f   V a r i a n c e -- design 1 * * * * * *

Tests involving 'FACTOR1' Within-Subject Effect.

AVERAGED Tests of Significance for A using UNIQUE sums of squares

Source of Variation	SS	DF	MS	F	Sig of F
WITHIN+RESIDUAL	16.06	9	1.78		
FACTOR1	591.69	3	197.23	110.51	.000

- -

Estimates for T2
--- Individual univariate .9500 confidence intervals

FACTOR1

Parameter	Coeff.	Std. Err.	t-Value	Sig. t	Lower -95%	CL- Upper
1	11.6834552	.58005	20.14214	.00027	9.83748	13.52943

- -

Estimates for T3
--- Individual univariate .9500 confidence intervals

FACTOR1

Parameter	Coeff.	Std. Err.	t-Value	Sig. t	Lower -95%	CL- Upper
1	-3.1250000	.71807	-4.35194	.02241	-5.41022	-.83978

- -

Estimates for T4
--- Individual univariate .9500 confidence intervals

FACTOR1

Parameter	Coeff.	Std. Err.	t-Value	Sig. t	Lower -95%	CL- Upper
1	1.28573909	.69747	1.84344	.16248	-.93391	3.50539

- -

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